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Cooling energy demand evaluation by means of regression models obtained from dynamic simulations

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ABSTRACT

The forecast of the energy heating/cooling demand would be a good indicator for the choice between different conception solutions according to the building characteristics and the local climate. A previous study (Catalina T. et al 2008) was focused on the estimation of heating demand. It is now presented a cooling demand evaluation study. In the early stages of a project, parametric studies have to be done to find an optimum solution among a large number of alternatives. To find a compromise between simple and complex methods of evaluating the cooling energy demand we have proposed to use energy regression models that can approximate with accuracy the results from the model to the data obtained from simulations. The regression energy equations were found to be a good way to quickly estimate the building cooling demand. Among the input data of these regression models it is mentioned the building morphology, sol-air temperature, thermal insulation level, windows U-value and windows surface.

INTRODUCTION

European Union has agreed a forward-looking political agenda to achieve its core energy objectives of sustainability, competitiveness and security of supply, by reducing greenhouse gas emissions by improving energy efficiency of the buildings. In a report realized by the „European Commission for Energy„ the major issues of EU citizens is the energy security which was translated by :

- shortages of fossil fuel supplies compared to increasing world demand
- high fossil fuel prices
- supplier or transit countries using their positions to exert political pressure
- inadequate energy efficiency measures in Europe„ or „impact of EU climate strategy.

The buildings sector – i.e. residential and commercial buildings - is the largest user of energy and CO_2 emitter in the EU and is the major energy consumer of the EU's total final energy consumption and CO2 emissions. Buildings account for 40–45% of energy consumption in Europe and China (and about 30–40% world-wide) (Day AR. et al 2009).

The forecast the energy heating/cooling demand would be a good indicator for the choice between different conception solutions according to the building characteristics and the local climate. A previous study (Catalina T. et al 2008) was focused on heating demand. We now present a cooling demand evaluation study But this energy demand is difficult to estimate given that the energy recovery becomes more complex and that the efficiency of the systems is directly influenced by the heating/cooling demand. Furthermore, estimating building energy demand is a big challenge knowing that it's almost impossible to model a true level of occupancy, lighting, and equipment loadings. The way in which a building and its services operates in practice is extremely complex and modelling it to obtain an accurate estimation of the energy consumption is very difficult. So, we need precise and easy to use support tools. In most of the cases in the early stages of a project, parametric studies have to be realized to find an optimum solution among a large diversity.

Different simplified methods were developed to evaluate the heating demand, like the degree-day method (Santamouris M. 2005) but they are not so accurate and in most of the cases they are over evaluating the energy demand.

Actually, the most reliable solutions are the simulation energy tools to estimate the impact of design alternatives and better understand the design problems with the respect to energy performance. Simulation tools are a good way to simulate and to analyze the building and the systems but this software tools demand however

a considerable amount of detailed input data and time from even an experienced user or in some cases powerful informatics equipments. Before or during a project design, multiple solutions should be proposed and studied but the lack of time and the complex data inputs stop this process of optimization and analysis.
To find a compromise between simple and complex methods of evaluating the heating/cooling demand is to use energy prediction models that can approximate with accuracy the results from the model to the data obtained from simulations or experimental campaigns.

This main research target of this article concerns the development of energy forecast models to evaluate the monthly/annual cooling demand for office spaces/classrooms, with the aim to be used by architects or design engineers as support tools in the very first stage of their projects in finding efficiently energetic solutions. Our attention will be directed towards the building design in terms of fenestration area and proprieties and its impact on the cooling demand.

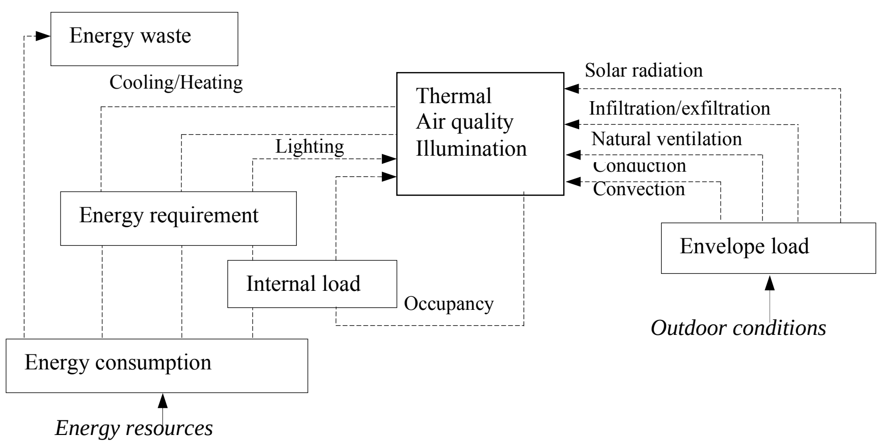

Figure 1. Energy flow and design concept process for buildings

The energy prediction model that were obtained in this research work simplify the parametrical studies and replace in the initial phase the numerical simulation tools in order to optimise the building energy consumption versus environmental or financial criteria. The developed methodology has its base structure on the energy flow and concept presented in Figure 1.

LITERATURE REVIEW

Different prediction models have been proposed by various researchers during the last years, including Fourier series models, regression models and neural network (NN) models. (Ruano et al. 2006) used NN technique to predict building's temperature based on the environmental data. Building energy consumption was forecast in tropical regions by (Dong et al. 2005) using a new NN algorithm and based on the data collected from four commercial buildings in Singapore. (Yang et al. 2005) proposed and tested two adaptive artificial NN to predict building energy consumption. The main benefits of artificial NN are that they are capable of adapting themselves to unexpected pattern changes in the incoming data.
When dealing with a certain pattern it is possible to use multiple regression analysis to obtain accurate models but is required a database to estimate the model parameters and the appropriateness of the statistical methods used to develop the equation. (Datta et al.1997) compared NN techniques to linear regression techniques and demonstrated that a simple linear regression model performs very poorly compared to a simple neural net. It was found that nonlinear models are substantially more accurate than linear models and a significant reduction of sum squared error is possible.

Based on the literature review it can be observed that there is a high interest on this subject with major potential and substantial advantages for the research and industrial sector. Our research work can be considered as a continuation of the previous researches work by focusing our attention on the office spaces and better taken into account the climate or the building morphology.

REGRESSION MODEL APPROACH

The objective of regression analysis is to predict the single dependent variable (cooling specific consumption) by a set of independent variables (e.g. windows to floor area ratio, climate coefficient and south equivalent surface). When having a large database of values like in our case, the regression techniques could be applied with success and with good results on the correlation between the model and the analyzed data set. The multiple regression shares all the assumptions of correlation: linearity of relationships, the same level of relationship throughout the range of the independent variable, interval or near-interval data, absence of outliers, and data whose range is not truncated. Developing a correlation method, it is essential to generate a large database by doing many parametric studies. Due to the large number of variations and cases, a considerably number of simulations (15.800 samples) was conducted to generate the database. The principle of a „black-box„ was used in this part where the inputs and outputs where first identified and then the process continued with the research of the „black-box„ curve-fit function. A „black-box„ model of a system is one whose internal structure is unknown and when the inputs/outputs are known and therefore is a question of "curve-fitting" by finding the most appropriate function (see Figure 2). Accurate knowledge of the consequence of parameters and the relationship between them is essential for optimal and feasible finding of the examined function.

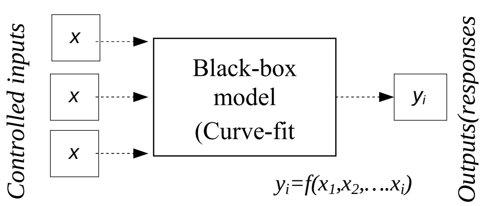

Figure 2. Black-box model example

Knowing that the models are wanted to be used for offices/classrooms building design a number of assumptions was made. The cooling indoor set point temperature was considered to be 26°C. The occupational period of the room is assumed to be from 8 a.m to 18 p.m only during the weekdays (Monday to Friday) .The heat gains are considered to be for 20W/m^2 (occupants and equipments) and 10 W/m^2 for the artificial lighting during the periods when the daylighting is not sufficient to ensure an illuminance level of 300 lx. The ventilation rate is assumed to be of 2 ach.

MODEL INPUTS/OUTPUT

The model output is considered to be the monthly cooling energy demand expressed in kWh/m^3. The following inputs were found to give a good curve fit approximation:

a) Climate

The first input of the thermal prediction model is the climate which was defined using the monthly sol-air temperature Tsol-air (Yumrutas et al., 2007) calculated from the values of hourly outdoor dry-bulb temperature and the global radiation on horizontal. Extreme climate conditions have been chosen in order to have a larger range of values. The minimum value was calculated to be -8.78°C (Moscow in January) and maximum of 42.9 °C (Abu-Dhabi in August). The hourly values of outdoor air temperature and solar radiation were obtained using Trnsys (Trnsys, 2006) meteonorm files.

b) Glazing surface and distribution

The window to floor area ratio (WFR) can be translated by a percentage from the occupied floor area of the total glazing area. The most appropriate size of a window for energy smart design depends on building orientation or the amount of thermal mass in the internal building materials. A WFR ratio of 15% to 18% is recommended in France, for conventional constructions and will balance the energy, first cost, and indoor environmental quality as proposed by the French Thermal Directive (CSTB 2005). Buildings implementing passive solar strategies using thermal mass and south orientation must be evaluated on an individual basis and may require a different overall WFR to achieve maximum benefit. The parametric study conducted on this input starts with lower values (5%) to higher ratios of 30 % glazing from the occupied floor area. The distribution of the glazing on the building/space façade has an obvious impact on the illuminance level and indoor heat gains, but to attempt a parametric study may be a challenging task. It is wanted to have a single input parameter that could define the glazing distribution and the orientation. The south equivalent surface (S_{es}) is used in order to solve half of this problem and it's definition by an older French Thermal Guideline is as follows:

$$S_{es} = \sum_{i=1}^{n} A_i \cdot C_i$$

Where A is the surface of the glazing and orientation coefficients C_i (see Table 1).

Windows orientation coefficients				
SSE to SSO	SSE to ESE and SSW to WSW	ESE to ENE and WSW to WNW	ENE to NNE and WNW to NNW	NNE to NNW
1	0.85	0.55	0.3	0.2

Table 1. Orientation C_i coefficients

Finally the used regression input is fenestration size and façade distribution factor $F_{s\text{-}d}$ defined as the S_{es} multiplied by the WFR.

c) Windows U-value

When designing the window, especially when trying to check the impact on the indoor conditions and energy consumption will be the fenestration coefficient of transmittance U_{win} which is our third input in the regression model.

d) Building morphology

Building morphology is an important factor that could influence an increase/decrease of energy required to heat or cool the occupied space. It was found a good solution to define the building or room geometry and implicitly the heat loss surfaces by using the $R_{s/v}$ input which is defined as the ratio between the sum of all heat loss surfaces that are in contact with the exterior, ground or adjacent non-heated spaces and the heated volume of the building/room. The greater the heat loss surface area, the more the heat losses through it, so higher ratios imply high energy demands.

e) Mean building insulation value

The building envelope insulation is a critical component of any facility because it plays a main function in the energy consumption and the regulation of the indoor environment. The French Thermal Standard (CSTB, 2005) defines the U_{bui} coefficient as the building envelope heat loss coefficient which is the average heat loss of thermal transmittance through building envelope including thermal bridges. The U_{bui} is calculated as follows:

$$U_{bui} = \frac{\sum (U_i \cdot A_i + \zeta_i l_i)}{\sum A_i}$$

where U_i is the thermal transmittance of building's components, A_i the corresponding surface, ζi the linear heat loss coefficient of building thermal bridges and l_i is the corresponding length.

In order to obtain the database necessary to identify the „black-box„ function, dynamic simulations were conducted using Trnsys 16 software (Trnsys, 2005). The Trnsys building model, known as, Type 56, is compliant with general requirements of European Directive on the energy performance of buildings and has been used with success by engineers to design efficient buildings, but also for scientific research.

Before approaching the regression analysis and the forecast models accuracy, a short presentation of the vocabulary used in the next part is enounced:

- <u>**A residual**</u> (or fitting error) is the vertical difference between the actual data points yi and the curve generated from the predicted values y'. If a residual is positive, it means that the actual data point lies above the curve and if takes a negative value that means that the actual data point lies below the curve. If the residual is zero, the actual data point lies on the curve (see Figure 2.13).
- <u>**The sum of residuals**</u> is the total sum of the residuals for all data points. If the curve passed through each data point, this sum would be zero; however, a regression model can have large positive and negative residuals and still sum to a small number.
- <u>**The standard error of the estimate**</u> is a measure of the accuracy of predictions. The standard error of the estimate is closely related to the sum of squared deviations and is defined below:

$$\sigma_{est.} = \sqrt{\frac{\sum (Y - Y')^2}{N}}$$

where $\sigma_{est.}$ is the standard error of the estimate, Y is the simulated value, Y' is the predicted value, and N is the number analyzed cases.
- <u>**The coefficient of determination**</u> is a measure of how well the regression line represents the data. If the regression line passes exactly through every point on the scatter plot, it would be able to explain all of the variation. A value of $R^2 = 1$ means that the curve passes through every data point and inverse when a value of $R^2 = 0$ means shows that the regression model does not describe the data any better than a horizontal line passing through the average of the data points.

In order to predict the space cooling demand (named y) as a function of the 5 selected parameters, different models have been studied. Based on the relationship between the parameters it shows that these elements are inter-connected; building morphology with the fenestration area and so on. These interdependences may be modeled by adding interaction terms to the polynomial equation, obtaining thus an interaction model:

$$y = \beta_0 + \sum_{i=1}^{5} \beta_i x_i + \sum_{i=1}^{5} \sum_{j=i+1}^{5} \beta_{ij} x_i x_j + \sum_{i=1}^{5} \beta_{ii} x_i^2$$

Once the form of the models was chosen, the next step consisted in the identification of the coefficients, β_i, which minimize the errors between the models outputs and the dynamic simulation results.

The model accuracy was evaluated by the mean of coefficient of determination (R2), the sum of residuals and the standard error of the estimate (SEE). For all the obtained models the R^2 had good values, higher than 0,99 and the max./min. residual were in acceptable limits. We paid attention to the analysis of residuals due to its importance to give clues about the appropriateness of the model used to fit the data. Histograms and scatter plots of residuals were studied to investigate the distribution of residuals. It was establish that the residuals are randomly scattered around zero and show no discernable pattern, without any relationship to the value of the independent variable. The following regression coefficients were found (see Table 2):

Regression coeff.	Value
β_0	-3.7222
β_1	0.0627
β_2	2.0363
β_3	0.2504
β_4	-6.2385
β_5	-1.0872
β_{1-2}	-0.0218
β_{1-3}	-0.0031
β_{1-4}	0.3006
β_{1-5}	0.0300
β_{2-3}	0.0126
β_{2-4}	-0.5801
β_{2-5}	-0.0938
β_{3-4}	0.0290
β_{3-5}	-0.0294
β_{4-5}	0.8581
β_{1-1}	0.0021
β_{2-2}	-0.2077
β_{3-3}	-0.0064
β_{4-4}	-1.3848
β_{5-5}	0.0962

Table 2. Model regression coefficients

Residual Sum of Squares (Absolute) = 664,30
Standard Error of the Estimate = 0,337
Coefficient of Multiple Determination **(R^2) = 0,9501**

MODEL STUDY CASE

To show the use of the model a 100m^2 (1076 ft^2) office room was analyzed. The height of the room is considered to be 3.2 m. The room is situated at the top floor with one external wall and the roof. The calculated Rs/v is 0.42 m^{-1} and the U_{bui} is assumed to be 0.35 W/m^{2}K. The U-window is 2.95 W/m^{2}K and the chosen climate is Paris (Tsol-air=19.45^{O}C – May to 26.06 ^{o}C in July). The window to floor area ratio is 18% and South equivalent surface of 18 m^2 (south orientation). The choice of the building model has to be made considering the local constructive and material uses. This model is then considered as a reference building and the results can be extrapolated for a large series of buildings, the energy demand being reported to the square meter of floor.
A first parametric study was done on the impact of WFR on the energy demand. As it can be noticed from Figure 3 a WFR of 26% compared to the 18% will increase by 19% the consumption. Other analysis was conducted on the impact of windows U-value. Triple glazing (Uwin=1.4 W/m^{2}K) will reduce the consumption by 36% (see Figure 4).

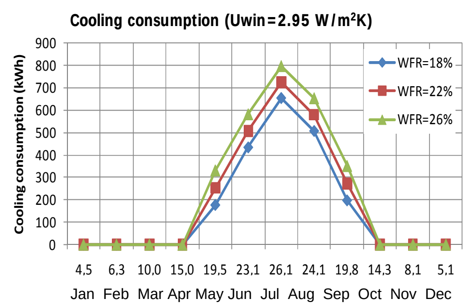

Figure 3. Impact of WFR ratio on the monthly cooling demand, with indication of monthly correspondent $T_{sol\text{-}air}$ temperature

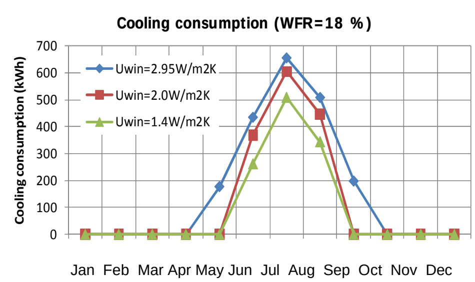

Figure 4. Impact of glazing U-value on the monthly cooling demand, with indication of monthly correspondent Tsol-air temperature

The glazing distribution may be a decisive design parameter knowing that can lead to significantly high changes in the energy balance (see Figure 5). With almost 25% higher values are obtained if the glazing is facing South compared to a North orientation.

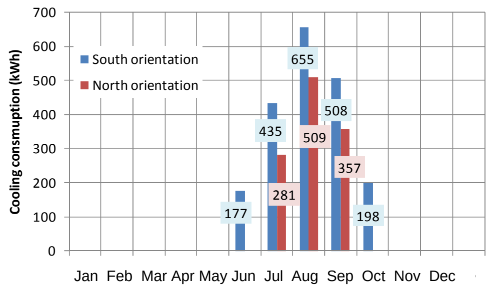

Figure 5. Impact of glazing distribution on the monthly cooling demand

CONCLUSIONS

In summary, it is concluded that the proposed prediction models show promising features to be easy and efficient forecast tools for comparing cooling demand of office spaces. Parametric studies are possible and energy efficiency measures can be easily proposed. The proposed model was based on a large number of simulations and the Coefficient of Multiple Determination (R^2) shows that the predicted values fit well the simulations values. The energy equations obtained on this study, associated with the one obtained in a previous study concerning heating demand (Catalina T. et al, 2008) could be used by architects and engineers during the early design stage of their project, instead of using more complicated and time consuming simulation software.

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